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An Efficient and Robust Corner Detection Algorithm*

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Abstract - **Corner detection has been shown to be extremely useful in many computer vision applications. In this paper, an improved SUSAN corner detector is proposed and its performance is compared with Harris and SUSAN corner detection. The method adopts an adaptive multi-threshold strategy based on local brightness rather than one threshold for the whole image, and divides the circular mask area of SUSAN into two or more parts. Next, the number of pixels in the part where the nucleus locates is calculated. If the number is less than half the total pixels of the circular mask, the nucleus will be a corner candidate. The exact positions of image corners are those candidates with local minimum numbers. In order to improve the computational efficiency of the algorithm, we limit the search space for corner candidates to those pixels whose intensity gradient magnitudes by Sobel operator are higher than a threshold. Experiments have demonstrated that our corner detector is accurate and efficient.**

Index Terms* – *Corner detection, adaptive multi-threshold, SUSAN corner detector.

I. INTRODUCTION

Corners are important features points of images. Their detection has become an essential and fundamental procedure in many computer vision problems, such as scene analysis, motion and structure from motion analysis, image registration, image matching, object recognition, etc. To yield satisfactory results, a corner detector should be able to detect all the true corners without generating false corners with the capability of precisely locating their positions, being robust to noises, and being sufficiently efficient for real-time applications.

Many algorithms have been reported for corner detection since the early time of computer vision research. Existing methods can be categorized into template-based corner methods and geometry-based corner methods [2]. A template-based method develops a set of corner templates and determines the similarity between the templates and all the sub-windows of a gray level image. Since multiple orientation templates are used, this method is computationally expensive.

Geometry-based method employs the differential geometry features to detect corners. Kitchen and Rosenfeld [3] proposed a corner measure based on the change of gradient direction along an edge contour at the local gradient magnitude. Wang and Brady [4] presented a corner detector based on surface curvature. Moravec [5] defined "points of interest" as points where a big intensity variation occurs in every direction. Harris and Stephens [6] modified the Moravec method and proposed the famous Harris corner detector by estimating the autocorrelation from the first-order derivatives. Rangarajan et al. [7] tried to find an analytical expression for an optimal function whose convolution with the windows of an image has significant values at corner points. Shilat et al. [8] worked on ridge's corner detection and correspondence. Nassif et al. [9] considered corner location measurement. Unfortunately, Most of the algorithms mentioned above are sensitive to noises because they use the image derivatives.

Smith and Brady [22] introduced a straightforward method called SUSAN (Smallest Univalue Segment Assimilating Nucleus) by extracting the portion of feature neighborhoods that is of similar intensity values. Given a digital image, the USAN area will reach a minimum when the nucleus lies on a corner point. The SUSAN algorithm has the advantages of being robust to noises and yielding accurate outcomes at a reasonable computation speed. However, this algorithm may generate false corners when the boundaries are blurry, i.e., the image contrast is low. Our experiments demonstrated that, as shown in Figure 4, false corners were generated even for a simple synthesized image.

In this paper, we present a new robust corner detector by improving the SUSAN algorithm in the following two aspects. First, we use local adaptive multi-threshold rather than a fixed one for the whole image. The SUSAN circular mask area is divided into two or more sub-areas by using the self-adaptive multi-thresholds. We determine the corners by counting the number of pixels of the sub-area where the nucleus locates. If the number is less than half the amount of the circular mask, the nucleus will be a corner candidate and the exact positions of image corners are those with local minima number. Second, we limit the search space for corners candidates to improve the computational efficiency. Since a corner is an end of an edge, we only search for corners from points on edges instead of the whole image. Experiment results demonstrated that the proposed corner method has a better performance than the Harris detector and the traditional SUSAN algorithm and can locate the corners more accurately.

II. SUSAN FEATURE DETECTION PRINCIPLE

Smith and Brady [10] proposed the SUSAN algorithm for corner detection, which successively processes the points of

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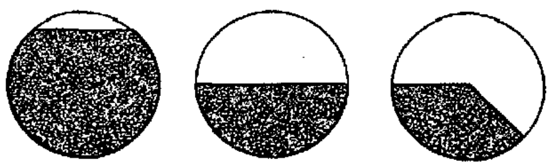
the input image. The point under examination is called nucleus in their paper. A corner point is judged based on gray level values of the pixels in a neighborhood of the nucleus. They used a circular mask with the center at the nucleus. In the mask, the pixels with approximately the same brightness as the nucleus are grouped and the area formed by them is referred to USAN (Univalue Segment Assimilating Nucleus). Three representative shapes of the USAN are shown on Figure 1. The USAN area reaches the maximum when the nucleus lies in a flat region of the image surface; it falls to half of the maximum when the nucleus is on a straight edge; and falls even further when the nucleus is a corner. The local minima of the USAN map represent the position of image corners. It is this property of the USAN's area that is used as the main determinant of the presence of edges or corners.



a *b* *c*

Fig. 1 Representative of USAN: a) nucleus is within the USAN; b) nucleus is an edge point; c) nucleus is a corner point.

Moving the circular mask through each point of the image, the intensity of each pixel within the mask is compared with that of the nucleus. A Simple equation determined this comparison is as follows:

$$c(\vec{r},\vec{r}_0)=\begin{cases}1 & if\left|I(\vec{r})-I(\vec{r}_0)\right|\le t\\ 0 & if\left|I(\vec{r})-I(\vec{r}_0)\right|>t\end{cases} \tag{1}$$

Where $I(\vec{r}_0)$ is the intensity of the nucleus, $I(\vec{r})$ is the intensity of any other pixel within the mask, t is the gray-level difference threshold and $c(\vec{r},\vec{r}_0)$ is the output of the comparison. This comparison is done for each pixel within the mask, and a running total of the outputs $c(\vec{r},\vec{r}_0)$ are as follows:

$$n(\vec{r}_0)=\sum_{\vec{r}\in c(\vec{r}_0)}c(\vec{r},\vec{r}_0) \tag{2}$$

Next, n is compared with a geometric threshold g. The feature response is created by using the following rule:

$$R(\vec{r}_0)=\begin{cases}g-n(\vec{r}_0) & if\ n(\vec{r}_0)<g\\ 0 & otherwise\end{cases} \tag{3}$$

This is clearly a simple formulation of SUSAN principle, i.e. the smaller the USAN area, the larger the corner response. Using different geometric threshold, the different features, such as corner, edge and junction, can be detected.

The outstanding advantage of SUSAN principle is the strong local noise rejection because it needs not use image derivatives and avoids intensity gradient. The integration effect of individual values in the calculation of areas of the principle, together with its non-linear response, reduces the effect of noise.

III. Improved SUSAN Corner Detection Scheme

In SUSAN corner detection, there are two thresholds: g and t. By using the geometric threshold g, we only consider those pixels that have smaller SUSAN area than g as corner candidates. This threshold can be fixed without tuning.

The threshold t determines the minimum contrast of features that can be detected, and the maximum amount of noise that can be ignored. The choice of t significantly affects the results. A small threshold t will pick up more subtle variations in the image and detects a greater number of candidate corners; a big value of t will neglect some corner. A proper value must be selected in order to trade-off between noise rejections and corner detection. Since it is difficult to find such a proper threshold automatically, we propose an adaptive method to calculate the threshold t based on local brightness of the circular mask area. Multi-thresholds are obtained by iterative approaches.

A. *Iterative Calculation of the Optimal Threshold*

The algorithm adopts an iterative process to calculate the threshold based on local contrast of the mask area. The iterative procedure classifies the pixels in the mask area as foreground and background according to their gray level intensity by using the optimal thresholding method. We can determine the optimal threshold [11] from the iterative process. The algorithm starts with the following initial selection of threshold:

$$T_0=\frac{I_{\max}+I_{\min}}{2} \tag{4}$$

Where I_{max} and I_{min} are the maximum and minimum values of gray level intensity among the pixels of the circular mask area, respectively.

The new threshold value is updated iteratively by the following equations:

$$T_{i+1}=\frac{1}{2}\left[\frac{\sum_{m=0}^{T_i}N_m\cdot m}{\sum_{m=0}^{T_i}N_m}+\frac{\sum_{m=T_i+1}^{L-1}N_m\cdot m}{\sum_{m=T_i+1}^{L-1}N_m}\right] \tag{5}$$

Where L is the numbers of gray levels, N_m is the numbers of pixels whose intensity value is m. T_i denotes the threshold at the i-th iteration. The iterative procedure is conducted until the optimal threshold is found when $T_{i+1}=T_i$. Thus a local optimal brightness difference threshold is obtained.

B. *Division of the Masks*

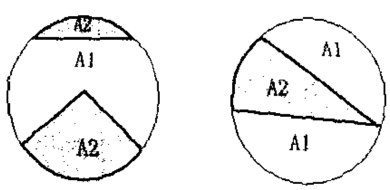
The SUSAN method divides the mask into only two parts. We think it is not adequate in some cases, For example, as shown in Fig. 3*a,* if the mask area is divided into only two parts, then we may fail to detect the corner because the USAN area (region A3 and A4) exceeds half of the mask. In fact, the nucleus is a corner in this case.

In our method, the mask must be divided into two or more parts according to its essential structure.

Based on the threshold obtained above, all pixels within the mask area are labelled by $A1$ and $A2$, respectively. Let us assume the numbers of pixels labelled as $A1$ and $A2$ to be $N1$ and $N2$, respectively, and the nucleus locates in area $A2$. If the two parts satisfy the following criteria:

- $Min\ (N1, N2) > 3$, we think 3 pixels can not form an area;
- area $A1$ must be 4-connected (All pixels in a 4-connected region can be reached one from other by one pixel moves of up, down, right, left). This criterion excludes those pseudo corner points whose USAN's areas are less than half of the mask area, as Fig. 2b shows.

The division can be regarded as reasonable. Otherwise, the division is regarded as unreasonable, and the nucleus is excluded from corner candidates. Figure 2a and 2b show an example of the reasonable and unreasonable division, respectively. In Fig. 2*a*, although region $A2$ is not 4-connected, the nucleus is a corner point, the division should be considered as reasonable, this is why in criterion 2 we only consider whether $A1$ is 4-connected or not.



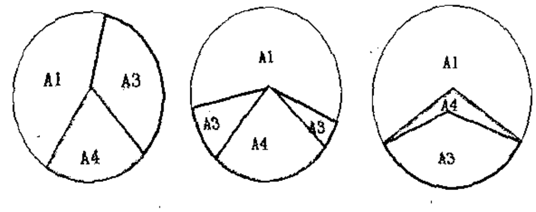
a *b*

Fig.2 *a*: reasonable division, and b: unreasonable division.

After the circular mask has been divided into area $A1$ and $A2$, we then decide whether the region $A2$ can be further segmented. A new threshold among the pixels of the region $A2$ is calculated by the method above described. Suppose $A2$ is segmented by this new threshold, and let the new area be A3, A4, and the numbers of pixels be $N3$ and $N4$, respectively, the nucleus locates in A4. If the two parts satisfy the following criteria:

- $Min\ (N3, N4) > 3$;
- both the area $A3$ and $A4$ must be 4-connected;
- both the centers of gravity of the area A3 and A4 must be located in their regions, respectively.

The division can be regarded as reasonable. Otherwise, the division is regarded as unreasonable. Fig. 3*a*, 3*b* and 3*c* show an example of the reasonable and unreasonable division, individually. In Fig. 3*a*, the total size of region $A2$ (namely $A3$ and $A4$) may exceed half of the mask area, but the nucleus is a corner point, the division should be considered as reasonable. In Fig. 3*b* and 3*c*, the size of $A2$ (namely $A3$ and $A4$) is less than half of the mask area already, further division will spoil the local minimum relationship that leads to false corner location. Thus, these cases should be thought as unreasonable division.



a *b* *c*

Fig. 3 *a*: reasonable division, and *b*, *c*: unreasonable division.

The division will continue till the divided two parts do not satisfy the criteria above described. Thus, if the nucleus is a corner candidate, its mask area will be divided into two or more parts. Then, the total number of those pixels with the same label as the nucleus is calculated. If the number is smaller than the geometric threshold g, we may regard the nucleus as a corner candidate. Furthermore, if the number is a local minimum, the nucleus is determined to be a corner.

In order to improve the computational efficiency, we limit the search for corners to some special pixels. Based on the fact that a corner is an end of edge, we only need to search for corners from points on edges instead of the whole image. Therefore, the algorithm first performs edge detection by simple Sobel edge operator and from the edges select points whose values of measure are above a threshold as corner candidates.

IV. Experimental Results

We have conducted experiments to compare the performance of our new corner detector with the Harris corner detector and the SUSAN corner detector. The experiments were performed on synthetic image and real images.

First, we compare the performance of these three corner detectors on a simple synthetic house image (Fig. 4). The object is of simple geometry. In Fig. 4, we can see clearly that 3 and 8 false corners were generated by the Harris and SUSAN detectors, respectively, and SUSAN detector missed 2 corners. However, no false corner was detected and no corner was missed by our algorithm. Moreover, our detector can locate the position of the corners more accurately than the other two. For the SUSAN algorithm the threshold t was set to 20. The results of testing are summarized in Table I.

Second, we test the three algorithms on a more complicated synthetic image. This image consists of many corner types, including L-Junction, Y-Junction, T-Junction, Arrow-Junction and X-Junction. It has been widely used to evaluate the corner detectors. Fig. 5 a) to c) show the corner images using the HARRIS, the SUSAN and our improved SUSAN detector individually. From the results, we can see that the new corner detector performed best on this synthetic image. All junctions have been correctly detected, as we expected. No false corners were reported. Harris corner detector missed one corner and detected 25 false corners. Susan corner detector spotted spurious corners when the angles are very sharp. One corner was missed and 3 false corners were detected. Here, the threshold t was set to 10. The results are summarized in Table II .

We also tested the corner detectors on a real image. This real image is a lab scene. There are many rectangles with well-defined corners in the image. The corner maps are shown as Fig. 6*a* to 6c. Our algorithm performed best in this test image. Almost all the corners were detected successfully. The Harris corner detector missed some corners that are corrupted by noise and reported some noisy points. Although SUSAN is less sensitive to noise, it missed many smoothed corners. The threshold t was to 15.

V. CONCLUSION

In this paper an efficient and robust corner detector is presented. This improved method can detect the features in different contrast images automatically through self-adjust multi-thresholds, which are iteratively computed based on local brightness difference. A comparison experiments demonstrate that the proposed method has better performance in corner detection and can localize corners' positions more precisely than Harris and SUSAN corner detectors. Therefore, we concluded that our algorithm is suitable for the corner detection with applications in image matching, 3D reconstruction from stereo images and etc.

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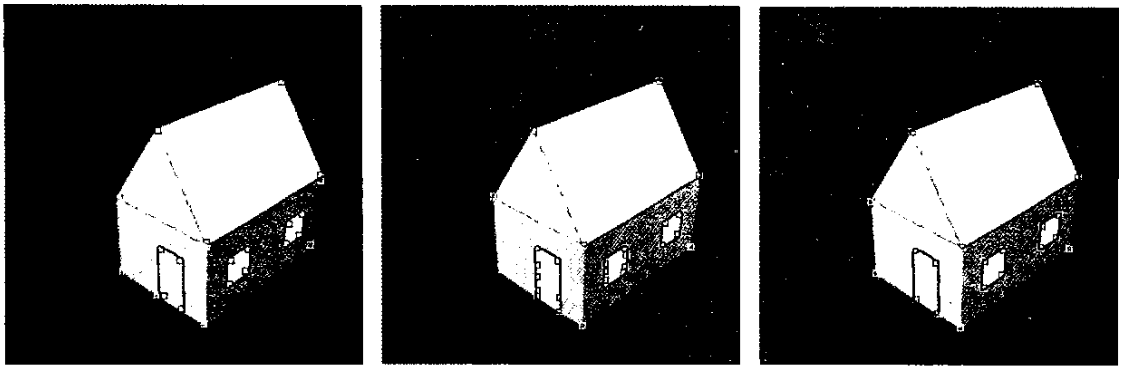
TABLE I
THE RESULTS OF TESTING FOR FIG. 4

Detector	Total Detections	Correct Detections	Corners Missed	False Detections
Harris	23	20	0	3
SUSAN	26	18	2	8
Our method	20	20	0	0

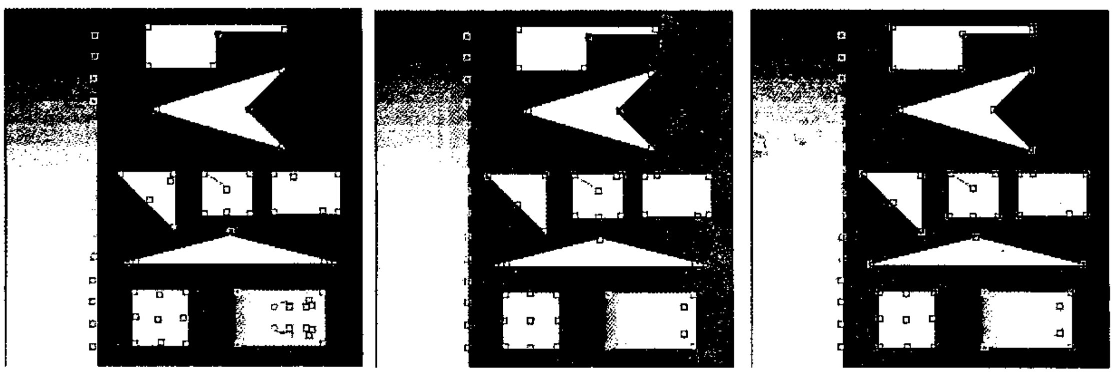
TABLE II
THE RESULTS OF TESTING FOR FIG. 5

Detector	Total Detections	Correct Detections	Corners Missed	False Detections
Harris	85	60	1	25
SUSAN	63	60	1	3
Our method	61	61	0	0



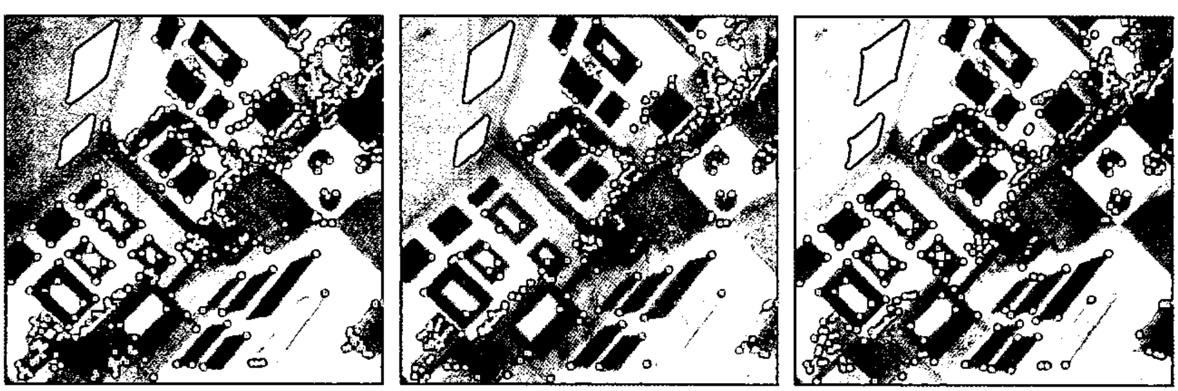
(*a*) (*b*) (*c*)

Fig. 4 Corner maps of the synthetic house image obtained by: (*a*) Harris Corner Detector; (*b*) SUSAN Corner Detector; (*c*) Improved SUSAN Corner Detector



(*a*) (*b*) (*c*)

Fig. 5 Corner maps of the synthetic image obtained by: (*a*) Harris Corner Detector; (*b*) SUSAN Corner Detector; (*c*) Improved SUSAN Corner Detector



(*a*) (*b*) (*c*)

Fig. 6 Corner maps of the lab indoor image obtained by: (*a*) Harris Corner Detector; (*b*) SUSAN Corner Detector; (*c*) Improved SUSAN Corner Detector